1 Quantitative analysis of spore shapes improves identification of fungi

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8 Abstract

9 Morphology of organisms is an important source of evidence for biodiversity assessment, taxonomic 10 decisions, and understanding of evolution. Shape information about zoological and botanical objects 11 is often treated quantitatively and in this form improves species identification. In studies of fungi, 12 quantitative shape analysis was almost ignored. The disseminated propagules of fungi, the spores, are crucial for their taxonomy - currently in the form of linear measurements or subjectively defined 13 14 shape categories. It remains unclear how much quantifying spore shape information can improve 15 species identification. In this study, we tested the hypothesis that shape, as a richer source of 16 information, overperforms size when performing automated identification of fungal species. We used the fungi of the genus Subulicystidium (Agaricomycetes, Basidiomycota) as a study object. We 17 18 analysed 2D spore shape data via elliptic Fourier and Principal Component analyses. With flexible 19 discriminant analysis, we achieved a slightly higher species identification success rate for shape 20 predictors (61.5%) than for size predictors (59.1%). However, we achieved the highest rate for a 21 combination of both (64.7%). We conclude that quantifying fungal spore shapes is worth the effort. 22 We provide an open access protocol which, we hope, will stimulate a broader use of quantitative 23 shape analysis in fungal taxonomy. We also discuss the challenges of such analyses that are specific to fungal spores. 24

25

26 Keywords

27 geometric morphometrics, classification, contour, fungi, outline, traditional morphometrics

28 Introduction

In eucaryotic organisms, morphology is an important source of evidence for biodiversity assessment, taxonomic decisions, and understanding of evolutionary and ecological processes. Morphological information is quickly accessible and can be processed at relatively low costs. Therefore it is broadly used by both researchers and citizen scientists. Morphological information, on the one hand, provides a starting point for molecular analyses, and on the other hand, serves as reference data to validate the molecular results [1].

35 Morphology covers two principal concepts: size and shape. The former is easier to measure and was 36 dominating for more than a century in the quantitative analyses known as traditional morphometrics 37 [2]. Although being important, the size alone is often insufficient for the delimitation of species or 38 populations. For example, within a single taxonomic group of diatom algae (Bacillariophyceae), linear 39 measurements allowed to delimit species in some genera [3] but not in others [4]. The authors of the 40 latter study concluded that involving quantitative shape descriptors, in addition to size, would make 41 delimitation of taxa more efficient. It is a discipline of geometric morphometrics that aims to quantify 42 a shape, geometric information about the object that remains after removing the effects of location, 43 rotation, and scale [5]. Tools of geometric morphometrics allow splitting the shape information into 44 symmetric and asymmetric components and analyse them separately [6]. Besides dealing with richer 45 data of numeric nature, geometric morphometric allows reconstruction of the original look of the 46 object after analyses – a valuable property that traditional morphometrics does not offer [1,2].

Fungi are among the species-richest organism groups on Earth [7]. Generally, for morphology-based fungal taxonomy, the features of the disseminated propagules, the spores, are of the highest priority among phenotypic characters [8]. However, there is a difference in how the size and shape of spores are usually treated. The spore size is routinely used for species delimitations, mostly in the form of quantitative traits such as length and width [9,10]. Spore shape also plays a big role but has been treated differently. The length to width ratio is used frequently as a proxy of the spore shape [9]. 53 However, it is based on linear measurements and has little use for reconstructing the full shape. In 54 most cases, spore shape is treated as a qualitative trait. Spore shape terminology in mycology is a 55 traditional system with dozens of terms that use common geometric shape categories ("globose", "cylindric") or similarity to some natural or cultural objects ("ovoid", "filiform"). The picture 56 57 becomes further complicated when subcategories are arbitrarily introduced, e.g. via adding prefix 58 "sub-" or epithets "slightly" or "almost". The subjectivity of this system represents a problem for 59 reproducible research. Furthermore, such an approach makes impossible an assessment of the 60 variation of a trait on an individual, populational, or species level. In their review, [1] concluded that "geometric morphometrics in the study of fungal shapes was far less employed compared to other 61 62 microscopic organisms". 63 To our knowledge, only two studies analysed the shape of fungal spores quantitively. Study [11] 64 found differences in the spore shape between the populations of one species and study [12] – 65 between the populations as well as different species. However, neither of these mycological studies 66 nor most other morphometric studies questioned in a quantitative way how the object's shape 67 performs compared to size when identifying species. An answer to this question would help to 68 decide how much effort should be invested into digitizing shape information for such small objects 69 as fungal spores. In this study, we test the hypothesis that shape, as a richer source of information, 70 overperforms size when performing automated identification of fungal species. If it is the case, 71 fungal spore shapes are worth the digitizing effort and integration into taxonomic workflows. To test 72 this hypothesis, we are going to answer the following questions: 73 (i) Is it possible to adequately extract the shape information from images of fungal spores 74 with the software that was developed for macroscopic objects? 75 (ii) Can the shape differences found in multivariate analyses be reconstituted as the

- 76 outlines and recognized by a human eye?
- 77 (iii) Is it justified to split the spore shape information into symmetric and asymmetric
 78 portions or analysis of the overall shape variation would suffice?

79 As a test system for our study, we will use the genus Subulicystidium Parmasto (Hydnodontaceae, 80 Trechisporales, Agaricomycetes, Basidiomycota, Fungi). It is a genus of fungi with 22 known species 81 [13]. All known Subulicystidium species have smooth crust-shaped (corticioid) fruiting bodies and 82 occur as saprotrophs on moderately or strongly decayed wood and are common in many forest 83 ecosystems, especially tropical ones. For this genus, we own a large set of spore images after our 84 previous study [14]. In that study, we performed traditional morphometric analysis of the spores 85 while treating spore shapes only qualitatively. An additional advantage of our test system is the 86 availability of DNA sequences for numerous specimens and the availability of the detailed genus-87 level phylogenetic tree. The DNA-based species assignments will serve as reference information to 88 compare the performance of shape versus size data for automated species identification.

89

90 Methods

91 DNA data

92 We used a balanced set of 30 herbarium specimens which included ten species of Subulicystidium 93 and where each species was equally represented by three specimens. We treated two clades of S. 94 perlongisporum described in [15] as two separate species "S. perlongisporum 1" and "S. perlongisporum 2". For all 30 specimens, we isolated and sequenced the internal transcribed spacer 95 96 (ITS) of the nuclear ribosomal DNA as described in protocol 1 in [15] or used the sequences we 97 produced earlier [14]. We processed raw sequence data with Geneious version 5.6.7 [16]. We 98 imported the edited sequences to R version 4.0.3 [17] with the package "Biostrings" version 2.58.0 99 [18] and performed the multiple sequence alignment with the package "msa" version 1.18.0 [19] 100 using MUSCLE algorithm [20] and other settings as default. We then customly trimmed the ends of 101 the alignment with the package "ips" version 0.0.11 [21] to the length when 15 of 30 sequences had 102 non-ambiguous base characters in the first and last position of the alignment. The resulting

103 alignment had 734 nucleotide positions. We used the alignment viewer available in the package 104 "ape" version 5.4.1 [22] to check visually the sequence alignment. According to the Akaike criterion [23], we identified "TrN+G+I" as the best-fitting nucleotide substitution model. We searched for the 105 106 best-scoring maximum likelihood phylogenetic tree with the nearest neighbor interchange strategy 107 and performed bootstrap analysis (1000 replicates) with the "phangorn" package version 2.5.5 [24]. 108 We visualized the result with the R package "ggtree" version 2.4.1 [25]. 109 We submitted the newly generated DNA sequences to GenBank [26]. We provide the full list of the 110 used DNA sequences with GenBank accessions and metadata on voucher specimens in supporting 111 information S1.

112

113 Morphological data

114 Spore terminology

115 To describe the spore morphology, we used the terms as they are found in [27] and [28]. The spores 116 in Subulicystidium, as in all Basidiomycota, are produced externally on a sporangium called basidium and remain attached to it till they become mature and ready for discharge (Fig 1). It is the proximal 117 118 part of the spore that directly contacts the basidium. The distal part of the spore is found on the 119 opposite side of its long axis. The spore has an adaxial side, i.e. turned to the main axis of basidium, 120 and opposite to it an abaxial side. On the proximal part of the spore, there is a projection called hilar 121 appendix that is involved in the spore discharge from a basidium [27]. Observing hilar appendix on 122 the adaxial side of the spore means the spore is seen in the lateral face. Observing hilar appendix directly on the main axis of the spore means the spore is seen in the frontal face. It is correct to 123 compare the shapes of the spores within the same face. In our study, we focus on the spore's lateral 124 125 face which is more informative in the case of Subulicystidium.

127 Fig 1. Crucial terms for describing a spore of the member of Agaricomycetes

128

129 Image acquisition and pre-processing

130 We acquired and pre-processed images from light microscopy as described in detail in our online 131 protocol [29]. In this paper, we highlight the most essential steps and we illustrate a workflow of 132 image processing in Fig 2. We performed all work on images on a desktop computer with 64-bit 133 Windows 10 operating system (build 19041). We obtained images of spores from squash preparations of fungal herbarium specimens examined at 1000× magnification (Fig 2A). The size of 134 135 the captured images (JPEG files) was 1024 × 768 or 2048 ×1536 pixels while the resolution was 136 always 96 dpi. We performed bulk image renaming with Bulk Rename Utility version 3.3.1.0 [30] and 137 conversion from JPEG to BMP graphic format with ImageMagick version 7.0.10-[31]. 138

139 Fig 2. Workflow showing the extraction of the shape and size information from a fungal spore.

140 (A) Image capture and pre-processing, (B) Acquiring linear measurements (C) Acquiring chain codes

141 (D) Transforming chain codes to Normalized Elliptic Fourier Descriptors (E) Checking quality and

orientation of the outlines (F) Possibility to open and manage outline descriptors in a text editor. The

tools and programs used at each step are named on the left side of each colored panel.

144

For further processing, we selected those images that contained one or several healthy (not broken, with intact cell wall) mature (not attached to basidia) and well-focused spores [29]. We selected also only the spores that were laying clearly in the lateral face. Furthermore, for meaningful shape analysis, spores had to be alignable, i.e. with hilar appendix stretching out to the same direction if the spore were placed in the same orientation. Some images had to be mirrored to meet this criterion. In some cases, we applied additional manual adjustments, namely painting white lines around some parts of the spore outline, to enhance the clarity of spore outlines and to ensure the absence of contact with the structures that are other spores or not spores (crystals or hyphae),

similar to [10] and [32]. These adjustments did not affect the geometric properties of the spore

154 outlines but enabled a correct outline extraction. Raw and pre-processed images and all information

155 extracted from them are available as a published dataset [33].

156

157 Processing shape information

158 Fungal spores are practically devoid of landmarks, i.e. distinct points that mark angles or cavities and

159 can be unambiguously assigned to an object. Therefore, for fungal spores, methods aiming to

160 reconstruct the complete outline are advantageous. Among such methods, Elliptic Fourier analysis

161 [34] is most commonly employed. It uses an ellipse as a starting shape and searches for the

162 coefficient values that transform the ellipse into the shape that reproduces the original outline of

the object. These coefficients are called Elliptic Fourier Descriptors. After normalization, i.e.

164 removing the effects of size, rotation, shift, and starting point of outline recording, they are called

165 Normalized Elliptic Fourier Descriptors (NEFDs) and are used in statistical analysis as variables

166 describing the shape [1].

167 We performed Elliptic Fourier analysis in the software package SHAPE version 1.3 [35]

168 (http://lbm.ab.a.u-tokyo.ac.jp/~iwata/shape/). We used consequently each of the following

169 programs from this package for different analysis steps: ChainCoder, Ch2Nef, NefViewer, PrinComp,

and PrinPrint [29]. We started with grayscaling the BMP images in the program ChainCoder (Fig 2C).

171 Then we converted the images to binary (assigning white pixels to spores and black to background)

based on a threshold that was mostly automatically selected by ChainCoder and was only rarely

adjusted manually. To remove the shape artifacts, we applied an erosion-dilation filter (that excludes

the noisy pixels from the outline) and rarely also a dilation-erosion filter (to fill in artifact cavities).

175 Then a chain code, i.e. a sequence of x and y coordinates describing the outline, was taken for each

176 spore.

177 We imported the chain codes to Ch2Nef program [35] and checked the orientation of all spores to 178 be the same, i.e. spore hilar appendix placed in the upper left quarter of the image (Fig 2D). When 179 necessary, we applied 180-degree rotation to some of the spores. Ch2Nef then transformed the 180 chain code into the Normalized Elliptic Fourier Descriptors (NEFDs). As a depth of detailsation of the 181 contour information, we opted for 20 levels that are called harmonics in the elliptic Fourier analysis 182 [34]. In general, other studies of organism shapes used from 15 to 30 harmonics [36,37], and using 183 20 harmonics was sufficient in the classical study from authors of the SHAPE package [6,35]. As each 184 harmonic is described by four coefficients (= Elliptic Fourier Descriptors), there were 80 coefficients 185 that characterised the shape of each spore. As the first three coefficients are always constant, there 186 were 77 coefficients serving as shape variables for the next analysis step. To normalize the Elliptic 187 Fourier Descriptors, we used the approach based on the first harmonic [35]. We checked that NEFDs 188 are alignable with the NefViewer program (Fig 2E).

189 We combined manually NEFDs for individual specimens into a single .txt file (Fig 2F). To reduce the 190 multidimensionality of NEFDs data, we run on it the Principal Component Analysis (PCA) in PrinComp 191 program [35]. We used the flexibility of PrinComp and performed in total three principal component 192 analyses (PCAs): i) considering only the symmetric shape variation, ii) considering only the 193 asymmetric shape variation, and iii) considering overall shape variation not differentiated into 194 symmetric and asymmetric (hereinafter called global shape variation). As a result of each PCA, we 195 retained those principal components (PC) that explained a substantial amount of variation and were 196 marked by PrinComp as having an eigenvalue >1. Such PCs were called "effective" in PrinComp. We 197 inspected visually the shape variation accounted for by each effective PC with PrinPrint program 198 [29]. The latter reconstructed the mean shape and plus and minus two times the standard deviation 199 shape for each principal component [35].

201 Processing size information

202	For exactly those spores for which NEFDs were obtained, we took also the linear measurement:
203	length (the longest dimension) and width (the broadest dimension) according to the standard
204	accepted in mycology [9]. We used Fiji distribution of ImageJ version 1.53c [38] as shown in Fig 2B
205	and described in [29]. Fiji does not differentiate whether the measurement is of a category "length"
206	or "width". Therefore, we measured constantly firstly length and then width or each spore. Though
207	these values were originally placed in a single column, we split them into length and width columns
208	in R using our protocol [29]. Based on length and width values, we also derived their ratio and used it
209	as an additional variable in statistical analyses.

210

211 Comparative analyses

While obtaining the shape descriptors and linear measurements, we had control of the number of 212 213 spores used per specimen and image. However, if the image contained several spores, we were not 214 able to align the shape descriptors with linear measurements for each particular spore. Even though 215 the input was the same .bmp image, the software for obtaining the shape data (SHAPE) and size data 216 (Fiji) named individual measurements slightly differently. We could overcome it only by producing 217 average-per-image trait values and using them as observations in correlations and discriminant 218 analysis [29]. To produce average-per-image trait values, we used regular expressions in R as well as 219 packages "stringr" version 1.4.0 [39] and "dplyr" version 1.3.0 [40]. 220 For comparison, we assigned the morphometric traits to one of the five categories: 221 i) principal components of symmetric shape variation 222 ii) principal components of asymmetric shape variation

- 223 iii) principal components of global shape variation
- 224 iv) linear measurements (length and width)

225 v) length to width ratio

226 We explored how similar were all morphometric traits between themselves by Spearman 227 correlations. To answer which morphometric traits allow more efficient automated identification of 228 fungal species, we applied discriminant analysis. We assessed how accurate the individual traits and 229 their combinations can identify (classify) to species level the observations whose species identity is 230 not known to the statistical model. We found that trait values within species are not necessarily 231 normally distributed and between the species do not have equal variance. For details, see supporting information S2 with the results of Shapiro-Wilk tests (made with R package 232 233 "RVAideMemoire" version 0.9-79, [41]) and Levene tests (made with R package "heplots" version 234 1.3-8 [42]). Therefore, we applied an appropriate for such cases flexible discriminant analysis [43] 235 implemented in "mda" R package version 05-2 [44]. We were randomly subsetting the data into the 236 train (70%) and test (30%) portions attempting to balance the presence of data for different species 237 with R package "caret" version 6.0-86 [45]. We repeated to subset the data into train and test 238 portions 1000 times and then calculated the average identification (i.e. correct species assignment) 239 success rate across subsettings using the R code adjusted from [46]. We managed data in R with the packages "here" version 1.0.1 [47], "conflicted" version 1.0.4 [48], 240 241 "readr" version 1.4.0 [49], "data.table" version 1.13.4 [50], "dplyr" version 1.3.0 [40], and "report" 242 version 0.2.0 [51]. We visualized the results with the packages "ggplot2" version 3.3.3 [52], "ggpubr" 243 version 0.4.0 [53], function "cor.mtest" [54] and package "corrplot" version 0.84 [55]. We edited Figs 244 1 and 4 with Inkscape version 0.92.5 [56] and Fig 2 also with Miro online whiteboard (https://miro.com/). We provide the R project with the code, input data and results of analyses in 245 246 supporting information S2 and as a repository on GitHub

247 (<u>https://github.com/ordynets/size_vs_shape</u>).

249 Results

250	Maximum likelihood phylogenetic analysis showed all ten Subulicystidium species on the
251	phylogenetic tree as clearly separate clades, mostly with high bootstrap supports (Fig 3).
252	
253	Fig 3. Phylogenetic relationship of 10 Subulicystidium species treated in this study
254	
255	After all quality filtering steps, we were able to analyse between 10 and 37 spores per specimen
256	which totaled 511 spores from 30 specimens. These spores were captured in 401 images and each
257	image contained one to four spores (supporting information S2). Therefore we considered 401
258	average-per-image values as observations for analyses.
259	PCA of symmetric shape variation identified only the first axis as effective (capturing 98,7% of the
260	variation in data) while PCA of asymmetric variation three first axes (capturing 83.03, 6.63 and 4.11%
261	of variation), and PCA of global variation two axes (capturing 94.57 and 2.91% of variation). Together
262	with the spore length, spore width, and length to width ratio, this summed up to nine traits which
263	we compared in terms of efficiency for automated species identification (supporting information S2).
264	By inspecting visually the shape variation accounted for by each principal component we found that
265	the 1 st PC of symmetric variation reflected well the relative thickness of spores (Fig 4). The 1 st PC of
266	asymmetric shape variation reflected the direction of single curving of the long axis of the spore. The
267	2 nd and 3 rd PCs of asymmetric shape variation reflected the variation in curvature of the proximal
268	and distal end of the spore, respectively. The effects of the 1^{st} and 2^{nd} PCs of the global shape
269	variation corresponded to the 1^{st} PC of symmetric and 1^{st} PC of asymmetric shape variation,
270	respectively.

271

Fig 4. Ranges of shape variation that separate principal components account for.

273

274	When correlating the individual trait variables, we found that 1 st PCs of symmetric, asymmetric, and
275	global shape variation correlated strongly positively with each other (Fig 5). All they correlated
276	strongly negatively with the length and moderately positively with the width of the spores. The 2^{nd}
277	PC of asymmetric shape variation correlated moderately negatively with the spore width while the
278	3 rd PC of asymmetric shape variation and 2 nd PC of the global shape variation did not correlate
279	significantly with any other trait. Length and width correlated moderately negatively between
280	themselves and each correlated very differently with the length to width ratio, though the
281	correlation was stronger between the length and length to width ratio.
282	
283	Fig 5. Spearman correlations of spore traits.
284	Colors show the direction of correlation and highlight only significant correlation values (at level
285	p=0.05)
285 286	p=0.05)
	p=0.05) In the discriminant analysis, the species identification success rate for the individual trait group was
286	
286 287	In the discriminant analysis, the species identification success rate for the individual trait group was
286 287 288	In the discriminant analysis, the species identification success rate for the individual trait group was highest for the global shape variation (61.5%, Fig 6) while was slightly lower for length and width
286 287 288 289	In the discriminant analysis, the species identification success rate for the individual trait group was highest for the global shape variation (61.5%, Fig 6) while was slightly lower for length and width (59.1%). Symmetric shape variation identified the fungal species better than the length to width
286 287 288 289 290	In the discriminant analysis, the species identification success rate for the individual trait group was highest for the global shape variation (61.5%, Fig 6) while was slightly lower for length and width (59.1%). Symmetric shape variation identified the fungal species better than the length to width ratio (57.9% vs. 53.8%). The asymmetric shape variation had the lowest identification success rate,
286 287 288 289 290 291	In the discriminant analysis, the species identification success rate for the individual trait group was highest for the global shape variation (61.5%, Fig 6) while was slightly lower for length and width (59.1%). Symmetric shape variation identified the fungal species better than the length to width ratio (57.9% vs. 53.8%). The asymmetric shape variation had the lowest identification success rate, viz. 46.9%. When combining the traits of different groups, the highest identification success rate was
286 287 288 289 290 291 292	In the discriminant analysis, the species identification success rate for the individual trait group was highest for the global shape variation (61.5%, Fig 6) while was slightly lower for length and width (59.1%). Symmetric shape variation identified the fungal species better than the length to width ratio (57.9% vs. 53.8%). The asymmetric shape variation had the lowest identification success rate, viz. 46.9%. When combining the traits of different groups, the highest identification success rate was achieved for the combination of symmetric, asymmetric shape variation and linear measurements

296 Fig 6. Species identification success rates in discriminant analysis for separate spore traits and

297 their combinations.

- Abbreviations on y axis: S = symmetric shape variation (first principal component), A = asymmetric
- shape variation (three first principal components), G = global shape variation (two first principal
- 300 components), LW = length + width, Q = length to width ratio, QLW = length to width ratio + length +
- 301 width, GLW = global shape variation + length + width, SALW = symmetric shape variation +
- 302 asymmetric shape variation + length + width.
- 303
- 304

305 Discussion

306	Quantitati	ve analysis of shapes helps to better identify and describe the organisms. In studies of		
307	fungi, despite their immense morphological diversity, quantitative shape analysis was almost			
308	ignored. In this study, we confirmed the hypothesis that shape, as a richer source of information,			
309	outperforms size during automated identification of fungal species by their spores. The highest			
310	identification success rate was achieved in a discriminant model that combined shape and size			
311	descriptors. The symmetric shape variation outperformed the classical length to width ratio. In			
312	general, we found that			
313	(i)	It is possible to adequately extract the shape information from microscopy images of		
314		fungal spores;		
315	(ii)	It is possible to recognise by a human eye the spore shape differences reconstituted		
316		after the multivariate analyses;		
317	(iii)	It is justified to split the spore shape information into symmetric and asymmetric		
318		portions for separate analyses.		

319 As quantitative shape analysis has been barely applied in mycology, we first had to ensure that 320 available tools for extracting shape information can be used for our goal. Many of the tools were 321 developed to work on the high-quality images of macroscopic organisms, often photographed as a 322 single object per image in the desired orientation [57–59]. We opted for the program package 323 SHAPE [35] which allows extracting several outlines from the same image, has flexibility for 324 performing PCA and in general, has a convenient interface and detailed manual. Despite this 325 package was originally designed for images of macroscopic objects, we successfully applied it to the 326 outline extraction from the images with a modest resolution made by our microscope camera. The 327 disadvantage of using SHAPE is a need to switch between the separate programs, meaning handling 328 several outcomes and an extra effort in data management. Furthermore, the graphical user interface 329 of SHAPE (or any other GUI program) means investing massive time effort when repeating the 330 analysis and increased risk of producing an error. Therefore, in the future, it is advisory to work in a 331 single environment with all analysis steps written as a code. This will simplify the data management 332 and enhance the reproducibility of the analyses. Functions in R language designed by [60] and 333 further developed by [61] and [62] are promising for this.

334 With our study design, we observed high correlations between several trait variables. The most 335 important to note is the correlation between the shape descriptors (PC1 of symmetric and 336 asymmetric variation) and size descriptors (especially length). This is due to our choice to represent 337 the size as linear measurements, which are known to be geometrically dependent on a shape [2]. 338 We kept linear measurements as size descriptors to demonstrate their properties and to explore the 339 performance of these classical variables for species identification. We also generated the size 340 variable that is a combination of separate linear measurements and is less independent of shape (square root of the product of length time width, as one possible option according to Claude 2008). 341 342 This size variable indeed correlated less with shape variables but in discriminant model predicted the 343 species much poorer than the length and width together (38.9% vs 59.1%, see supplementary 344 information S2). In geometric morphometrics, there are also other measures of the size that are

345 independent of shape and are worth the look by fungal taxonomists [60,63]. Among other trait 346 variables, the correlation between PC1 of global and symmetric shape variation, PC1 of global and 347 asymmetric shape variation, and length and length to width ratio are easily explained by their nested nature. Therefore we did not add these highly correlating variable pairs to the same discriminant 348 349 models. On the other hand, we struggled to explain the rather high correlation between PC1 of 350 symmetric and asymmetric shape variation. We guess that it is due to a strongly dominating 351 character of PC1 of symmetric shape variation, which was constructed with an account of the firstlevel elliptic Fourier harmonic (D1). 352

353 The identification success rate in our discriminant analyses reached the maximum value of 64.69%. It 354 is hard to compare our results with other studies where authors used different traits and/or 355 different classification methods. Benyon et al. (1999) achieved an identification success rate of 356 66.2% using seven traits and a higher rate (74.4%) using 20 traits of fungal spores (mostly size 357 descriptors). Authors of [4] obtained similar to our results in discriminant analyses of size and 358 texture traits in diatom algae (55.1% correctly identified items). Authors of [65] reached 100% or 359 nearly such rates for species of diatom algae by shape and texture descriptors. However, they used 360 discriminant analysis as a dimensionality reduction tool and above its result applied other 361 classification techniques. Authors of [66] evaluated their analyses of diatom cell shapes visually, i.e. 362 as strength of separation of observations in the space of discriminant functions. They concluded that 363 taxa with distinct shapes were separated well while the taxa with similar shapes were separated to a 364 less extent. The identification success rates in [32] for statoliths in cubomedusae were comparable, 365 after cross-validation, with ours, but were highly dependent on the number of observations per 366 group. Due to technical reasons explained in Methods section, we performed analyses on average-367 per-image data. We admit that working with spore-level data would provide a more precise estimate 368 of the correct identification rate.

369 Future work on quantitative shape analysis of fungal spores should cope with several challenges. 370 Fungal spores may have very different outline properties in lateral versus frontal face. In the current 371 study, we focused on the lateral face which is more peculiar in *Subulicystidium* and allows to capture 372 the curvature along the spores' long axis (while the frontal face masks this feature). However, in 373 other fungal taxa, the lateral and frontal faces are both important [28] and their shapes should be 374 analysed with the same attention. Authors of [32] combined three faces of the objects to achieve a 375 high identification success rate. In fungi, it may be easy to identify the spore as exposed in the lateral 376 face if its hilar appendix is large enough. Unfortunately, this is not the case for all species. Special 377 care should be taken to identify the position of the hilar appendix in the needle-like spores (as in S. 378 cochleum and S. perlongisporum in our dataset). Applying scanning electron microscopy may help to 379 identify correctly the hilar appendix but also to get a detailed picture of the surface of the fungal 380 spore. While our study focused on the fungi with smooth spores, the latter in many taxa bear 381 additional projections like warts or ridges or distinct spines. These elements would be difficult to 382 capture with the elliptic Fourier descriptors because of the mathematical properties of the method 383 [1]. Therefore, ornamented spores of fungi give a chance to bring another approach, landmark-384 based methods of geometric morphometric, to mycology. These can be implemented in a twodimensional and even three-dimensional space. Finally, different properties of the spores in lateral 385 386 versus frontal face, as well as the availability of the several spore types per species in many fungal 387 lineages, offer a possibility to bring the machine learning techniques to mycology.

388 We conclude that quantifying fungal spore shapes is worth the effort. We provide an open access 389 protocol to propagate a broader use of quantitative shape analysis in fungal taxonomy and to 390 stimulate the development of more efficient solutions to address the challenges we discussed above.

392 Data Availability

- 393 Metadata on studied voucher specimens is provided in supporting information S1. DNA sequences
- newly generated for this study are available from GenBank as accessions MW711723-MW711729.
- 395 Raw and pre-processed images and all information extracted from them are available as a published
- dataset (Ordynets et al. 2021b, https://doi.org/10.15156/BIO/807451). The R project with the code,
- input data, and results of analyses is provided in supporting information S2 and as a repository on
- 398 GitHub (<u>https://github.com/ordynets/size_vs_shape</u>).
- 399

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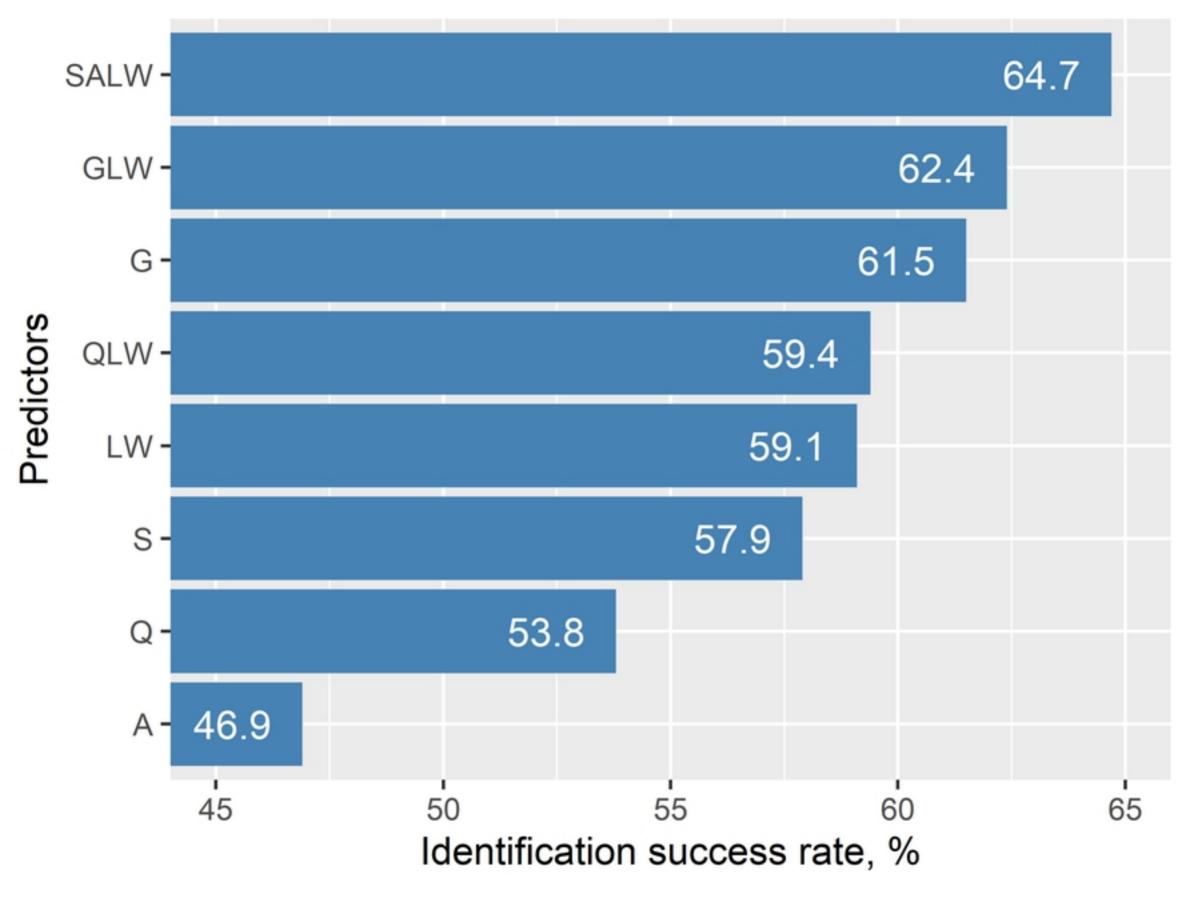
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559 Supporting information

- 560 S1 Table. GenBank accessions of used DNA sequences and metadata on voucher specimens
- 561 S2 Appendix. R project with the code, input data, and results of analyses.



Spore in lateral face

Spore in frontal face

